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Gender divides in teachers' readiness for online teaching and learning in higher education: Do women and men consider themselves equally prepared?

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ABSTRACT

During the last years, the "Great Online Transition" has brought to light large variation in teachers' readiness for online teaching and learning (OTL). Drawing from an international sample of 731 higher-education teachers, we examined gender differences in OTL readiness as a source of this variation. Currently, in the field of OTL, better evidence is needed to understand the associated dimensions and effects of gender on teachers' experiences and perceptions of readiness, to provide better support and professional learning opportunities in transitioning to an online and blended practice. To provide such evidence, we first evaluated the measurement bias in the readiness measures and found support for strong gender invariance. Second, we quantified the gender differences in readiness levels: Women reported higher readiness for cognitive activation practices ($d = +0.15$); men reported higher self-efficacy in technological content knowledge ($d = -0.20$). These gender differences were small, varied across readiness constructs, and were due to a gender gap in OTL experience. Third, construct associations involving perceived institutional support were weaker for women. To improve the quality, robustness, and validity of the respective evidence, we argue that studying gender divides in OTL readiness needs to consider measurement bias, OTL experience, and construct associations.

1. Introduction

During the last few years, the "Great Online Transition" (Howard et al., 2022) has forced university teachers around the world to adopt online teaching and learning (OTL) within a short period of time (Cutri et al., 2020). In this context, OTL refers to digital remote teaching substituting face-to-face teaching in physical classrooms by using digital devices in online environments (Brooks & Grajek, 2020). This transition has brought to light large variation between teachers in the extent to which they considered themselves prepared for OTL—including variation in self-beliefs, how they facilitated high-quality online teaching, and the support teachers received at their institutions (e.g., Núñez-Canal et al., 2022; Scherer et al., 2021). Teachers who report similar institutional support and engage in similar online teaching practices may not report the same level of confidence in OTL (e.g., Howard et al., 2020; Scherer et al., 2021).

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The extant literature has identified teachers' gender as a key source of this variation (e.g., Korlat et al., 2021; Šabić et al., 2021). However, the directions and sizes of such gender differences vary largely, with some studies reporting women's or men's higher self-efficacy in teaching with technology (e.g., Hung, 2016; Martin et al., 2019), and other studies reporting no gender differences (e.g., Adnan, 2017; Eslaminejad et al., 2010). Uncovering, quantifying, and explaining this variation is critical for tailoring support and professional development to teachers' needs (Alamri et al., 2021; Bolliger & Halupa, 2022). Gender can indicate a range of factors relating to teachers' experiences and is therefore an important dimension to understand in teacher change, professional learning and support. Our study contributes to this body of knowledge and adds novel evidence on gender differences in teachers' readiness for OTL.

Obtaining credible and reliable evidence on possible gender differences is, however, complex. Specifically, comparing women's and men's levels of OTL readiness requires that the readiness measures are comparable across gender in their underlying measurement model (Scherer & Siddiq, 2015)—this perspective of *measurement bias* is key to drawing valid conclusions about possible gender effects (Millsap, 2011). Moreover, reports of gender differences have largely focused on the levels of readiness. Yet, differences may also occur in the associations among readiness constructs, such as self-efficacy or perceived institutional support for OTL—this perspective is key to understanding the interplay between different facets of readiness (Hanham et al., 2021). Finally, identifying possible causes and mechanisms through which gender differences operate represents a critical element of understanding the nature of these differences. Some studies have identified teachers' experience as a potential explanatory (i.e., mediating) variable (Šabić et al., 2021)—this perspective of *OTL experience* is key to interpreting the context of gender differences (Klassen & Chiu, 2010).

In the present study, we argue that taking the perspectives of measurement bias, OTL experience, and construct associations can improve the quality, robustness, and validity of the evidence base on such gender differences. Taking the three novel perspectives, we uncover, quantify, and explain gender differences in higher-education teachers' readiness for OTL and provide evidence for the validity of these differences and where they lie.

2. Theoretical background

2.1. The concept of teachers' readiness for OTL

Teachers' readiness for OTL represents a broad construct that has been defined in many ways. While readiness represents a general "state of faculty preparedness for online teaching" (Martin et al., 2019, p. 97) that has sometimes been assumed to be unidimensional (e.g., Chua & Chua, 2017; Paliwal & Singh, 2021), it also includes specific knowledge and skills, attitudes and beliefs, and facilitating conditions (e.g., Cutri & Mena, 2020; Graham et al., 2013). A systematic search for studies measuring teachers' readiness for OTL suggested that most studies represented the construct by multiple factors (e.g., Chou & Chou, 2021; Hung, 2016; Scherer et al., 2022): (a) Knowledge, skills, and competence; (b) instructional practices; and (c) the support teachers experience at their institutions. Similarly, in their review, Cutri and Mena (2020) synthesized the diverse conceptualizations of OTL and identified affective dispositions, organizational orientations, and pedagogical approaches as core elements. The existing conceptualizations of teachers' readiness for OTL consider the concept to be multidimensional, covering, among others, self-beliefs, perceived support, and teaching presence.

In recent studies, researchers indicated **teachers' self-beliefs in teaching with technology** as part of their readiness by drawing from the technology-related dimensions of the Technological and Pedagogical Content Knowledge (TPACK) framework (e.g., Brinkley-Etzkorn, 2018; Lachner et al., 2019; Voogt et al., 2013)—a framework that captures multiple knowledge domains (see Koehler et al., 2014). Specifically, the technology-related, content-oriented, and pedagogical TPACK dimensions include TCK (i.e., knowledge about the ways of representing teaching content with technology), TPK (i.e., knowledge about the instructional use of technology), and TPCK (i.e., knowledge about the interplay between pedagogy, teaching content, and technology). While these dimensions correlated highly in some studies (e.g., Scherer et al., 2021), they were empirically distinct in other studies (e.g., Schmid et al., 2020). These findings point to the existence of a general TPACK factor that captures the communalities among TCK, TPK, and TPCK, but also to the existence of specific factors that capture the unique components of TPACK dimensions (Scherer et al., 2017).

Successfully creating **online teaching presence** is also key to high-quality OTL (Scherer et al., 2021). Online teaching presence includes social, teaching, and cognitive presence (Law et al., 2019) and utilizes teaching practices, such as learner-learner interaction, assessment and feedback, cognitive activation, and instructional clarity (Gurley, 2018; Kreijns et al., 2022). Ultimately, teaching presence in OTL creates a sense of connectedness and forms the basis for supportive and engaging learning environments (Rapanta et al., 2020; Shea et al., 2006).

The **institutional** support **teachers perceive** is another key component of OTL readiness (e.g., Chou et al., 2020; Cutri & Mena, 2020). Institutional support can facilitate creating a shared vision for OTL and can thus motivate teachers to adopt it as a form of teaching (e.g., Scherer et al., 2019; Tondeur et al., 2019). Institutional support can also facilitate collaboration among teachers and thus improve their teaching practices (e.g., Blömeke et al., 2021; Yu et al., 2021). During the GOT, institutional support was critical to the adoption of OTL, especially the aspects of digital leadership, vision building, pedagogical support, and technological guidance (Damşa et al., 2021; Mittal et al., 2021).

2.2. Gender differences in OTL readiness

2.2.1. Technology-related self-beliefs, teaching practices, and perceived support

Examining gender differences in teachers' **technology-related self-beliefs**—that is, their self-confidence, self-efficacy, and self-concept—has been in the interest of researchers for some decades (Scherer et al., 2019; Teo, 2014), and significant gender differences in technology-related self-beliefs are considered to be indicators of a digital gender divide (Saikkonen & Kaarakainen, 2021). This large body of evidence abounds in sometimes conflicting findings, with gender differences that vary substantially in size, significance, and direction across studies, teacher samples, research designs, countries, and constructs—however, men tended to show higher self-beliefs in technology domains than women in many studies (Ergen et al., 2019). For instance, the International Computer and Information Literacy Study (ICILS) 2013 showed gender differences in ICT self-efficacy in favor of men for nine participating countries; nevertheless, gender differences were in favor of women in one country, and three countries did not identify any gender differences (Gebhardt et al., 2019). Hung (2016) found that men held higher learning-transfer self-efficacy ($d = -0.32$); however, there were no gender differences in communication self-efficacy. Utilizing a large-scale and representative sample of Norwegian teachers, Scherer and Siddiq (2015) found that men had higher self-efficacy in basic ($d = -1.03$) and advanced ($d = -0.49$) applications of technology, while there was no such evidence for self-efficacy related to teaching with technology. Countering the latter finding, Gómez-Trigueros and Yáñez de Aldecoa (2021) reported large differences in TPACK self-efficacy in favor of men (TCK: $d = -4.35$; TPK: $d = -1.96$; TPCK: $d = -3.16$). Furthermore, Scherer et al. (2017) discovered that gender differences in self-efficacy measures focusing on technological knowledge (TK) favored men and tended to be larger ($d = -0.54$) than in the measures focusing on the pedagogical and didactical aspects of teaching with technology ($d = -0.29$). The large-scale sample of Singaporean teachers studied by Koh et al. (2010) exhibited a similar tendency (TCK: $d = -0.28$; TK: $d = -0.45$). Ergen et al. (2019) supported this observation meta-analytically for 27 primary studies on Turkish teachers' TPACK self-efficacy (e.g., TK: $d = -0.34$; TPCK: $d = -0.11$). Overall, these findings indicate that gender divides in teachers' technology-related self-beliefs may exist in favor of men, depending on the context of these self-beliefs (i.e., technological vs. teaching focus).

Gender differences in the **reported online teaching practices** that are aimed at creating online presence have also been documented. The ICILS 2013 data showed that female teachers tended to include technology more often into their classroom practices (except for three countries) and emphasized the development of digital skills to a larger extent. Similarly, Nikolopoulou and Kousloglou (2022) found that women provided feedback to students and cognitively activating tasks more frequently than men ($ds = 0.06$). Perera and John (2020) supported this by showing that female teachers achieved better student-student interactions during their math lessons ($d = 0.46$). Focusing on OTL contexts, Scherer et al. (2021) reported that women engaged more frequently in practices to achieve better online presence ($ds = 0.10$–0.17). This selection of studies points to the existence of gender differences in reported teaching practices in favor of women (see also Supplementary Material S1).

Concerning teachers' perceptions of **institutional support**, gender differences may either be small or non-existent. Several studies found similarities across gender in the perceived technological support and the support for OTL by supervisors, principals, or colleagues (e.g., Huffman et al., 2013; Hung, 2016; Nikolopoulou & Kousloglou, 2022; Özgür, 2020). In contrast, Scherer et al. (2021) found a significant yet small effect size in teachers' perceptions of the technological and pedagogical support in favor of women ($d = 0.05$).

The extant literature provides an impressive body of evidence on digital gender divides in the perceived levels of OTL readiness. However, this focus falls short of exploring gender differences in other relevant aspects of readiness, such as the associations between readiness constructs (Hahn et al., 2022). Construct associations are key elements in a nomological network as they define how different dimensions of constructs interact (Cronbach & Meehl, 1955). A recent meta-analysis by Zeng et al. (2022) indicated that the relation between teachers' TPACK self-efficacy and their technology integration was not moderated by the gender distribution in the study samples. If technology integration is considered a dimension of readiness, then this study did not find significant gender divides in its association to TPACK self-efficacy, another readiness dimension. However, technology integration is oftentimes used as a result or outcome of teacher readiness (Scherer & Teo, 2019). Despite our efforts in reviewing the existing literature systematically, at the time of writing, we could not identify empirical studies that examined and reported explicitly gender differences in the associations between multiple readiness constructs (see Supplementary Material S1).

2.2.2. Explaining gender differences by measurement bias

Despite the large body of evidence, the validity of gender differences in OTL readiness has rarely been examined (for a systematic overview, please see Supplementary Material S1). Specifically, survey scales with multiple items that capture readiness constructs can function differently across gender, so that reported differences in readiness levels may not reflect true gender differences but also the differential functioning of readiness indicators (e.g., Eagly & Revelle, 2022; Teo, 2014). This issue represents a form of measurement bias and can compromise the validity of the inferences drawn from reported gender differences (AERA APA & NCME, 2014). The differential functioning or "non-invariance" of readiness indicators across gender may have several causes, such as gender-sensitive formulations or contents of the indicators favoring one gender over the others (Millsap, 2011). Some authors in the field of educational technology have showed that assessments of teachers' readiness, especially the self-belief dimension, can be prone to such differential functioning and thus bias or partly explain the reported gender differences (e.g., Hatlevik et al., 2017; Scherer et al., 2017). It is therefore key to examine whether such bias exists and to account for it.

2.2.3. Explaining gender differences by experience

Existing gender differences in teachers' readiness for teaching with technology have attracted researchers to explore possible causes or mechanisms through which they operate. While the reasons and processes behind such differences are complex, the existing body of research provides some explanations beyond measurement bias: Huffman et al. (2013) argued that gender differences in teachers' technology-related self-efficacy are due to differences in the self-perceptions of knowledge and skills and in the perceived gender roles and identities. These gender roles may manifest in different subject cultures and socializations of teaching, that is, teaching orientations toward mastery or performance (Lauermann & König, 2016).

Moreover, self-beliefs rely on mastery experiences of teaching in general (Morris et al., 2017) and while integrating technology (Barton & Dexter, 2020). Indeed, some studies suggested that readiness is associated with teachers' experience with technology-based teaching (e.g., Backfisch et al., 2020; Hung, 2016; Scherer et al., 2022). Hence, possible gender differences in experience could explain gender differences in OTL readiness (Šabić et al., 2021). Landino and Owen (1988) tested this hypothesis for a random sample of faculty and a measure of self-efficacy. They found that gender differences in self-efficacy were partly explained and thus mediated by gender differences in experience indicators. Despite the evidence on gender differences in OTL readiness and experience and the experience-readiness relation (see Supplementary Material S1), to our best knowledge, this hypothesis of experience mediation has not yet been tested in the context of OTL.

3. The present study

Gender differences in constructs that indicate teachers' readiness for teaching with technology have long been in the interest of researchers, and a plethora of empirical studies reported such differences (e.g., Borokhovski et al., 2018; Cai et al., 2017; Qazi et al., 2022). Our brief review of the extant literature indicated that: (a) Gender differences varied in size, significance, and direction across teacher samples, studies, and readiness measures; (b) gender differences were mainly reported in the readiness levels; and (c) the explanatory role of OTL experience for gender differences in readiness levels is largely unexplored. However, three key perspectives have largely been ignored while reporting and interpreting gender differences in technology-related attitudes, beliefs, and motivation—the perspectives of *measurement bias*, *OTL experience*, and *construct associations*.

In the present study, we test for gender differences in teachers' readiness levels, accounting for possible bias in the readiness measures (see Fig. 1).

RQ 1. To what extent do the levels of teachers' OTL readiness differ across gender after controlling for measurement bias?

Reported gender differences may have several causes or mechanisms through which they operate (Klassen & Chiu, 2010). Given that OTL readiness is often represented by self-perceptions and self-beliefs, teachers' experience with OTL—a key source of these perceptions and beliefs (e.g., Hung, 2016; Scherer et al., 2022)—may explain the gender differences (e.g., Perera & John, 2020; Siddiq & Scherer, 2016; Šabić et al., 2021). In the present study, we examine whether teachers' OTL experience explains (i.e., mediates) possible gender differences in OTL readiness (see Fig. 1).

RQ 2. To what extent does teachers' OTL experience explain (i.e., mediate) the gender differences or similarities in the levels of OTL readiness?

Finally, gender differences have been mainly explored in the levels of constructs, focusing on the extent to which teachers, on average, differ in their (perceived) readiness. In the present study, we examine gender differences in the associations between readiness constructs (see Fig. 1).

RQ 3. To what extent do the relations among the readiness constructs differ across gender?

Overall, we argue that taking the perspectives of measurement bias, OTL experience, and construct associations extends the existing body of research on gender differences in OTL readiness and improves the quality, robustness, and validity of the respective evidence. Fig. 1 displays our respective research questions.

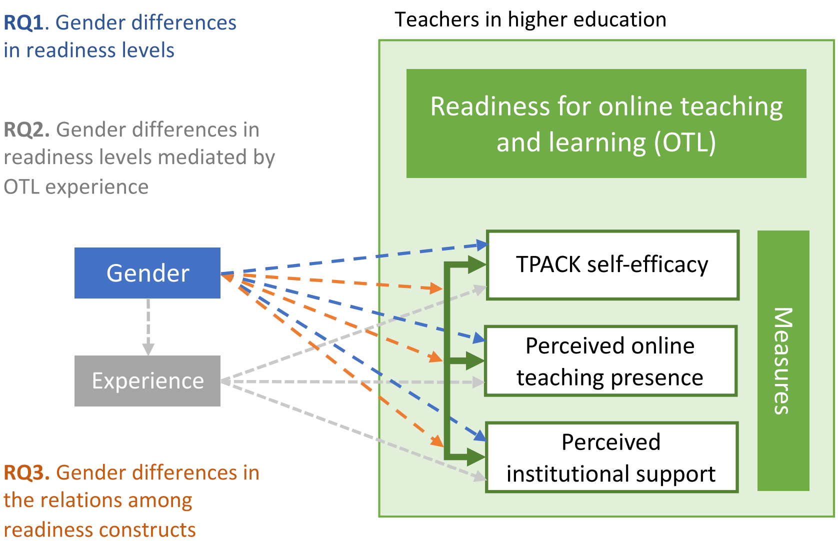

Fig. 1. Research model underlying the study of gender differences in teachers' OTL readiness.

4. Method

4.1. Sample and procedure

Between March and May 2020, we invited pre- and in-service teachers around the world to participate in our online readiness survey at the outset of the COVID-19 pandemic. Of the more than 900 respondents, 731 teachers worked in higher-education institutions (universities and colleges) in 58 countries and, after informed consent, provided data on their background characteristics, teaching experience, the teaching context, and readiness for OTL. On average, teachers had 19.5 years of experience in the profession ($SD = 10.8$), and 5.9 years of experience with OTL ($SD = 5.7$). About 80.6% of the teachers had to transition their face-to-face or blended teaching to fully OTL as a response to the COVID-19 pandemic in March 2020, and they were given 6.8 days on average to achieve this. Table 1 shows the detailed sample characteristics.

4.2. Measures

We assessed teachers' personal readiness for OTL focusing on three core constructs: (a) TPACK self-efficacy; (b) perceived online teaching presence; and (c) perceived institutional support. Please find the respective reliability coefficients in Table 2 and the item wordings in Table A1 in the Appendix.

4.2.1. TPACK self-efficacy

Focusing on the technological pedagogical and content-related dimensions of the TPACK framework, we assessed teachers' self-efficacy in their TCK, TPK, and TPCK, using an adapted version of Archambault and Crippen's (2009) measure (see also Scherer et al., 2021). This measure captured self-efficacy in TCK by two items (e.g., "I am confident in my ability to implement the curriculum in an online environment"), TPK by four items (e.g., "I am confident in my ability to encourage online interactivity among students"), and TPCK by four items (e.g., "I am confident in my ability to use technology to create effective representations of content that departs from textbook knowledge"). Teachers responded using a 5-point agreement scale (*0 = I strongly disagree*, *4 = I strongly agree*). The internal consistencies of the TPACK item sets ranged between omega-hierarchical $\omega_h = 0.79$ and 0.80 (for details about this reliability coefficient, please see Flora, 2020).

4.2.2. Perceived online teaching presence (POTP)

To capture core aspects of online teaching practices, we assessed teachers' perceptions of the online presence they created during OTL. These aspects included the clarity of instruction (e.g., "I can clearly communicate important course goals"; POPCLA, 4 items), cognitive activation (e.g., "I help to keep course participants on a task in a way that helps students to learn"; POPCOG, 7 items), and feedback and assessment (e.g., "I provide feedback that helps students understand their strengths and weaknesses relative to the course goals and objectives"; POPFED, 2 items). These aspects were based on previous empirical studies supporting their associations and differentiation (e.g., Gurley, 2018; Howard et al., 2020). All items had 5 agreement response categories (*0 = I strongly disagree*, *4 = I strongly agree*), and the internal consistencies of the subscales ranged between $\omega_h = 0.85$ and 0.87 (see Table 2).

Table 1
Description of the teacher sample.

Teacher characteristic	*n*	Proportion
Gender		
Women	397	54.3%
Men	334	45.7%
Subject domains		
Arts and Humanities	99	13.5%
Social Sciences	238	32.6%
Medicine and Health Sciences	66	9.0%
Engineering	126	17.2%
Science	82	11.2%
Business	80	11.0%
Law	21	2.9%
Missing information	19	2.6%
World regions (The World Bank, 2020)		
Europe & Central Asia	615	84.1%
East Asia & Pacific	37	5.1%
Latin America & Caribbean	19	2.6%
Middle East & North Africa	19	2.6%
North America	18	2.5%
South America	9	1.2%
Sub-Saharan Africa	14	1.9%
Experience with Online Teaching and Learning		
Some OTL experience	272	37.2%
No OTL experience	459	62.8%

Note. $N = 731$.

Table 2
Descriptive statistics and correlations of the readiness constructs.

Variable	M	SD	n_I	ω_h	1	2	3	4	5	6
1. Perceived institutional support (gPIS)	2.89	1.20	8	0.88	1.00					
2. TCK self-efficacy	2.92	0.85	2	–	.40	1.00				
3. TPK and TPCK self-efficacy (TPK-TPCK)	2.60	0.79	8	0.79	.42	.88	1.00			
4. Perceived online teaching presence: Clarity of instruction (POPCLA)	3.17	0.67	4	0.85	.36	.78	.71	1.00		
5. Perceived online teaching presence: Feedback (POPFED)	2.81	0.86	2	–	.34	.60	.65	.73	1.00	
6. Perceived online teaching presence: Cognitive activation (POPCOG)	2.66	0.77	7	0.87	.41	.68	.80	.77	.79	1.00

Note. Readiness constructs were represented as latent variables in the final CFA measurement model. n_I = Number of indicators, ω_h = McDonald's omega-hierarchical (reliability coefficient; e.g., Flora, 2020). *M* and *SD* refer to the mean and standard deviation of the manifest scale scores (i.e., average item responses per readiness construct). All correlations were statistically significant at the 1% level. TPACK self-efficacy and perceived online teaching presence: Teachers responded to these items on a 5-point agreement scale (*0 = I strongly disagree*, *4 = I strongly agree*). Perceived institutional support: Teachers indicated their agreement to these items on a 6-point scale (*0 = I completely disagree*, *5 = I completely agree*). *N* = 731.

4.2.3. Perceived institutional support (PIS)

The measure of perceived institutional support captured teachers' perceptions of the extent to which their universities supported the adoption of OTL in general (e.g., "In our institution, there is a supportive environment as regards professional development for online learning"; 6 items) and specifically at the beginning of the COVID-19 pandemic (e.g., "Additional technical support has been provided to transition face-to-face teaching to online because of COVID-19"; 2 items). The generic PIS questions were based on Philipsen's (2018) Institutional Support for Online and Blended Learning (ISOBL) scale for which a validity argument had been crafted recently (e.g., Philipsen et al., 2022; Scherer et al., 2022). Teachers indicated their agreement to the items on a 6-point scale (*0 = I completely disagree*, *5 = I completely agree*). Scale reliability was high, $\omega_h = 0.88$.

4.3. Statistical approaches

4.3.1. Analytic setup

To address our research questions, we performed structural equation modeling (SEM)—a multivariate analytic approach that allows for (a) quantifying group differences in constructs while accounting for possible measurement bias; (b) examining group differences in the relations among constructs; and (c) testing these differences for mediators and moderators (Kline, 2016). Within SEM, we accounted for possible deviations from normality and the continuous treatment of item responses with at least five response categories (e.g., Rhemtulla et al., 2012; Robitzsch, 2020) by utilizing robust maximum-likelihood estimation. We obtained robust standard errors (Savalei & Rosseel, 2022) and the Yuan-Bentler-scaled chi-square statistic, YB-χ^2 (Yuan & Bentler, 2000). The proportion of missing item responses was small (*Mdn* = 0.4%, *Max* = 1.8%), and we handled them via the full-information-maximum-likelihood procedure (Enders, 2010). In our study, teachers from different countries participated. Given the nesting of teacher data in countries, we corrected the standard errors and test statistics. The respective intraclass correlations were small (ICC_1: $M = 0.083$, $SD = 0.050$, $Mdn = 0.080$).

All statistical models were evaluated according to their fit to the data. Specifically, we applied the following evaluation criteria for an acceptable model fit (Hu & Bentler, 1999; Savalei, 2018): (a) insignificant YB-χ^2 statistic ($p > .05$); (b) robust Comparative Fit Index

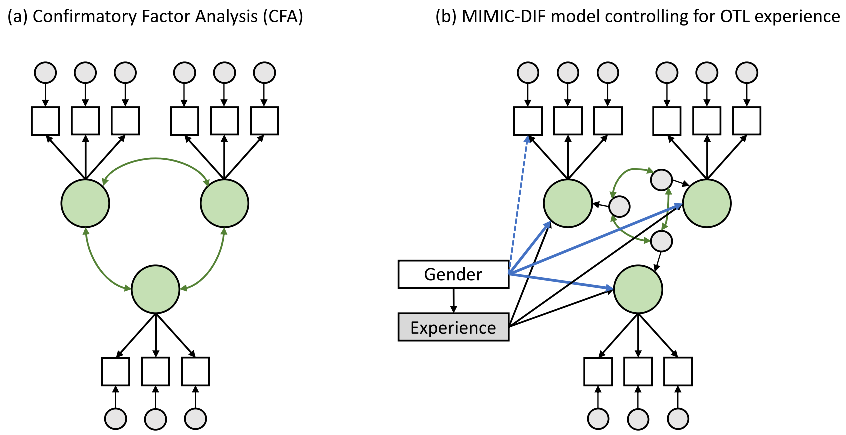

Fig. 2. Analytic Models Used to Describe Gender Differences in the Readiness Levels and the Relations among Readiness Constructs. *Note.* Circles represent latent (unobserved) variables; squares and rectangles represent manifest (observed) variables. MIMIC-DIF = Multiple-Causes-Multiple-Indicators Model with Differential Item Functioning.

(CFI_r) ≥ 0.95; (c) robust Root Mean Square Error of Approximation ($RMSEA_r$) ≤ 0.06; and (d) Standardized Root Mean Squared Residual (SRMR) ≤ 0.08. Despite their popularity, these criteria, however, do not represent "golden rules" (Marsh et al., 2004), because they depend on the model estimation procedure, setup, size, and other factors (e.g., Shi et al., 2018). McNeish and Wolf (2021) developed a simulation-based procedure to obtain dynamic cut-offs for the RMSEA, CFI, and SRMR. We adopted this procedure and obtained such cut-offs from the web application "Dynamic Model Fit" (Wolf & McNeish, 2020). All structural equation models were estimated in the R packages "lavaan" (Rosseel, 2012) and "semTools" (Jorgensen et al., 2021).

4.3.2. Structural equation models

In a first step, we established a measurement model for teachers' OTL readiness via confirmatory factor analysis (CFA; see Fig. 2a). This measurement model contained multiple correlated factors that represented the readiness constructs (i.e., TPACK self-efficacy, perceived online teaching presence, and perceived institutional support) as latent variables and was based on prior research on the structure of readiness scales (e.g., Hung, 2016; Scherer et al., 2021).

Second, we extended this measurement model to a multi-group CFA model to test if the prerequisites for comparing readiness levels and relations across gender were fulfilled. Whenever group comparisons of construct levels or relations are conducted, it is key to establish that group differences are due to actual differences in the factor means or correlations, yet not in other model parameters (Millsap, 2011). To test if this was the case, we performed measurement invariance testing by estimating and comparing a series of multi-group CFA models with different equality constraints (Putnick & Bornstein, 2016). These models represented adjacent levels of invariance (e.g., Marsh et al., 2009): (a) *Configural invariance* with the same setup of the measurement model across gender (i.e., the same number of factors and loading patterns); (b) *Metric invariance* with equal factor loadings across gender; (c) *Scalar invariance* with equal factor loadings and item intercepts across gender; (d) *Strict invariance* with equal factor loadings, item intercepts, residual variances and covariances across gender; (e) *Structural invariance* with the strict equality constraints and equal factor variances and covariances across gender; and (f) *Factor means invariance* with the equality constraints of the scalar, strict, or structural invariance models and equal factor means across gender. To accept an invariance model, the difference in chi-square statistics between two adjacent models should be insignificant ($p > .05$), with minimal differences in fit indices ($\Delta CFI \leq -0.01$, $\Delta RMSEA \geq 0.015$, and $\Delta SRMR \geq 0.010$; Chen, 2007). At least partial metric invariance (with some factor loadings that can vary across groups) must hold if comparisons of construct relations are conducted, and at least partial scalar invariance (with some intercepts that can vary across groups) must hold if construct levels are compared (Brown, 2015).

Third, we supplemented the invariance testing with an analysis of uniform differential item functioning (DIF) to identify non-invariant readiness indicators. This analysis was necessary, because the multi-group CFA only tests the invariance of model parameters globally; yet, it does not capture well the possible local deviations from this constraint for specific items (Bauer, 2017). We used multiple-indicators-multiple-causes models to test the indicators for uniform DIF (i.e., MIMIC-DIF models) and inspected the Benjamini-Hochberg adjusted *p*-values (p_{BH}) to uncover non-invariant indicators (Hatlevik et al., 2017; Woods, 2009). These MIMIC-DIF models allowed us to quantify possible gender differences in the readiness constructs, account for non-invariant readiness indicators, and include OTL experience as a possible explanatory variable of the gender differences (see Fig. 2b).

To address **RQ1**, we checked if the readiness measurement model was at least scalar-invariant via multi-group CFA. If this was the case, we quantified the gender differences via MIMIC-DIF models which accounted for possible measurement bias.

To address **RQ2**, we extended the MIMIC-DIF models by teachers' OTL experience and examined the evidence of its explanatory role for the gender differences in readiness constructs.

To address **RQ3**, we examined the equality of factor correlations by testing for the structural invariance of the readiness measurement model via multi-group CFA.

4.3.3. Open science practices

We pre-registered the variable selection and analytic plan of our study in the Open Science Framework at [https://doi.org/10.17605/OSF.IO/PH5VY]. The analytic code, input and output files, and the Supplementary Material are openly accessible on the respective project page, [https://doi.org/10.17605/OSF.IO/EU9QW].

5. Results

5.1. Descriptive statistics, readiness measurement model, and factor correlations

The readiness indicators (i.e., item responses), were not substantially skewed (see Appendix Table A1). To create a representation of the readiness constructs with these indicators, we estimated a CFA model of readiness with seven correlated factors, each of which represented one readiness construct (i.e., three TPACK self-efficacy constructs, three perceived online teaching presence constructs, and one perceived institutional support construct). This model showed an acceptable fit to the data (YB-χ^2 [393] $= 922.5$, $p < .001$, $CFI_r = 0.971$, $RMSEA_r = 0.042$, $SRMR = 0.031$), yet contained a high correlation between TPK and TPCK self-efficacy ($\rho = 0.99$). Hence, we re-specified the model by collapsing TPK and TPCK self-efficacy into one factor, "TPK-TPCK". The resultant model showed an acceptable fit to the data (YB-χ^2 [399] $= 931.8$, $p < .001$, $CFI_r = 0.971$, $RMSEA_r = 0.042$, $SRMR = 0.032$) and did not deteriorate the fit of the initial model (YB-$\Delta\chi^2$ [6] $= 9.1$, $p = .17$). We therefore accepted the more parsimonious CFA model with six instead of seven correlated factors as the readiness measurement model.

The correlations among the readiness constructs were positive and ranged between $\rho = 0.34$ (perceived institutional support and online presence via student feedback) and $\rho = 0.88$ (TCK and the TPK-TPCK self-efficacy factor). Notably, correlations to perceived institutional support were the smallest ($\rho = 0.34$-0.42; see Table 2).

5.2. Gender differences in OTL readiness levels (RQ1)

We first performed measurement invariance testing, specifying a series of multi-group CFA models with equality constraints on the model parameters (see Table 3). The configural model served as the baseline for further invariance models and exhibited good fit indices, YB-χ^2 [798] = 1594.9, $p < .001$, CFI$_r$ = 0.961, RMSEA$_r$ = 0.050, SRMR = 0.037. Up to the strict invariance model, the fit indices did not deteriorate substantially, and the respective changes were within the suggested cut-offs (see Table 3). As a consequence, metric, scalar, and strict invariance held. However, further constraining factor covariances and variances deteriorated the model fit (e.g., Δ SRMR = +.011 when comparing the strict and structural invariance models). Further constraints on the factor means to the structural invariance model did not change the fit indices. Comparing the strict and a refined factor means invariance model (i.e., a model imposing the equality of factor means in addition to the strict invariance constraints) did not deteriorate model fit beyond the suggested cut-offs (see Table 3). Hence, we considered the readiness measurement model to be strictly invariant, and thus gender comparisons of the readiness construct levels were possible.

Women reported significantly lower TCK self-efficacy ($d = -0.17$, $p = .04$) and higher levels of perceived online teaching presence via cognitive activation ($d = +0.16$, $p < .01$). The levels of all other readiness constructs were statistically equal across gender (perceived institutional support: $d = +0.05$, $p = .40$; TPK-TPCK self-efficacy: $d = 0.00$, $p = .99$; perceived online teaching presence via instructional clarity: $d = +0.09$, $p = .21$; perceived online teaching presence via student feedback: $d = +0.18$, $p = .13$; see Supplementary Material S4). Although these effect sizes were controlled for possible subject differences in readiness, we also tested for gender differences in readiness *within* each of the seven subject domains. However, the sample sizes within the subject domains were small, and the respective effect sizes were error-prone and unsystematic across readiness dimensions (see Supplementary Materials S4 and S5).

However, the gender differences could still be prone to measurement bias in some readiness indicators (DIF). We therefore tested for the non-invariance of item intercepts via MIMIC-DIF models. Please find the respective outcomes in the Supplementary Material S2. Overall, we found that four readiness items exhibited DIF.

- TPK1 ("*I am confident in my ability to create an online environment which allows students to build new knowledge and skills.*") with $d = +0.12$, $p_{BH} = 0.005$
- POTP2 ("*I clearly communicate important course goals*") with $d = -0.07$, $p_{BH} = 0.010$
- POTP12 ("*I provide feedback that helps students understand their strengths and weaknesses relative to the course goals and objectives*") with $d = +0.14$, $p_{BH} < 0.00001$
- POTP13 ("*I provide feedback in a timely fashion*") with $d = -0.14$, $p_{BH} < 0.00001$

Positive DIF effects suggested that women reported higher levels of this readiness indicator after controlling for gender differences in the readiness constructs. Conversely, negative DIF effects suggested that men reported higher levels of this readiness indicator. All other indicators were invariant (see Supplementary Material S2).

Table 3
Gender invariance testing of the readiness measurement model.

Model	Equality constraints	YB-χ^2 (*df*)	CFI$_r$	RMSEA$_r$	SRMR	YB-$\Delta\chi^2$ (Δ *df*)	ΔCFI$_r$	ΔRMSEA$_r$	Δ SRMR
Configural	Struc	1594.9 (798)*	.961	.050	.037	–	–	–	–
Metric	Struc, FL	1651.3 (826)*	.959	.050	.043	56.5 (28)*	−.002	.000	+.006
Scalar	Struc, FL, Int	1689.5 (851)*	.959	.049	.043	39.3 (25), p = .03	.000	−.001	.000
Strict	Struc, FL, Int, ResVar, ResCov	1792.0 (899)*	.955	.050	.044	100.4 (48)*	−.004	+.001	+.001
Structural	Struc, FL, Int, ResVar, ResCov, Fvar, Fcov	1842.4 (920)*	.953	.050	.055	50.5 (21)*	−.002	.000	+.011
Factor means I	Struc, FL, Int, ResVar, ResCov, Fvar, Fcov, Fm	1869.4 (926)*	.952	.051	.056	27.4 (6)*	−.001	+.001	+.001
Factor means II#	Struc, FL, Int, ResVar, ResCov, Fm	1821.6 (905)*	.954	.050	.045	34.3 (6)*	−.001	.000	+.001

Note. YB-χ^2 (*df*) = Yuan-Bentler-scaled χ^2-statistic with *df* degrees of freedom, CFI$_r$ = robust Comparative Fit Index, RMSEA$_r$ = robust Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Squared Residual. Struc = Structural setup (i.e., number of factors, assignment of item indicators to factors), FL = Factor loadings, Int = Item intercepts, ResVar = Indicator residual variances, ResCov = Indicator residual covariances, Fvar = Factor variances, Fcov = Factor covariances, Fm = Factor means. Adjacent models were compared. # This model was compared to the strict invariance model. *$p < .01$.

In a next step, we estimated the gender differences in the readiness constructs again and adjusted them for the DIF effects. To achieve convergence, however, only three of the four DIF effects could be included. As a result, gender differences in TCK self-efficacy ($d = -0.20$, $p = .009$) and perceived online teaching presence via cognitive activation ($d = +0.15$, $p < .001$) were statistically significant. All other gender differences were insignificant (see Fig. 3).

5.3. Gender differences controlled for OTL experience (RQ2)

Addressing RQ2, we extended the MIMIC-DIF model by OTL experience (see Fig. 2b). This model had an acceptable fit to the data, YB-χ^2 (448) = 1061.7, $p < .001$, CFI$_r$ = 0.968, RMSEA$_r$ = 0.042, SRMR = 0.031. Gender differences in OTL experience existed in favor of men, $b = -0.09$, $SE = 0.02$, $p < .001$. Introducing OTL experience deteriorated the significance of the gender differences in TCK self-efficacy (see Fig. 3). Except for perceived institutional support and instructional clarity practices, the gender differences in readiness constructs were mediated by OTL experience, as the significant indirect effects suggested (for the detailed effects, see Supplementary Material S3 and S4). We also tested the mediation hypothesis within the seven subject domains. Similar to the gender differences, the mediation effects were again unsystematic and prone to measurement and sampling error (see Supplementary Material S5).

Specifically, the relations between teachers' gender and the readiness constructs TPK-TPCK self-efficacy and perceived online teaching presence via student feedback were fully mediated by OTL experience. The relations were partially mediated for TCK self-efficacy and perceived online teaching presence via cognitive activation. For the latter, the partial mediation was competitive, that is, the direct and indirect effects neutralized each other to some extent and had different signs; for the former, the partial mediation was complementary, that is, the direct and indirect effects complemented each other and had the same sign (Fig. 4). Hence, gender differences in the readiness constructs could be partly explained by teachers' OTL experience.

5.4. Gender differences in the relations among OTL readiness constructs (RQ3)

To examine possible differences in the relations among the readiness constructs, we tested the equality of factor covariances and variances across gender. Specifically, we compared the strict invariance model to a model in which the covariance matrix of latent variables was constrained to be equal between women and men ("structural invariance"). Table 3 shows the resultant fit indices of this model. Except for the chi-square statistic, all other indices were acceptable. However, the SRMR and the chi-square difference test indicated that the model fit deteriorated when adding the structural equality constraints to the strict invariance model, Δ SRMR = +0.011, YB-$\Delta\chi^2$ (21) = 50.5, $p < .05$. Hence, this model comparison suggested gender differences in the factor covariance structure.

Fig. 5 displays the factor correlations for women and men. These matrices show gender differences in the correlations between (a) perceived institutional support and TPACK self-efficacy; (b) perceived institutional support and perceived online teaching presence for feedback and, respectively, cognitive activation; and (c) TCK self-efficacy and perceived online teaching presence for feedback and, respectively, cognitive activation. Correlations were smaller for women, leaving perceived support less connected to the other readiness constructs.

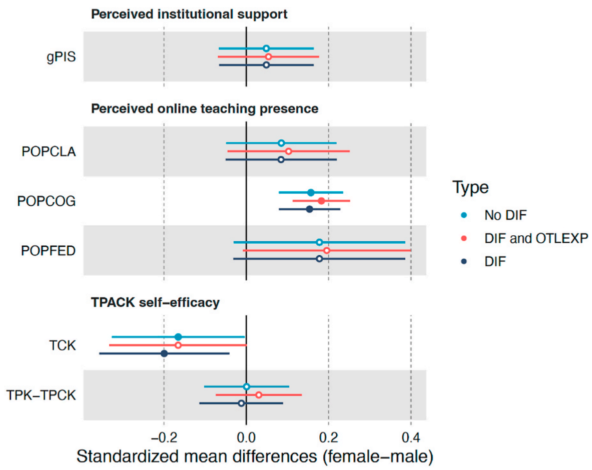

Fig. 3. Gender Differences in the Readiness Constructs. *Note.* gPIS = General factor representing perceived institutional support, TCK = TCK self-efficacy, TPK-TPCK = TPK and TPCK self-efficacy, TPK = Technological pedagogical knowledge, TPCK = Technological pedagogical content knowledge, POPFED = Perceived online teaching presence: Student feedback, POPCLA = Perceived online teaching presence: Clarity of instruction, POPCOG = Perceived online teaching presence: Cognitive activation. DIF = Effect size accounted for differential item functioning, OTLEXP = OTL experience. Effect sizes with a filled circle are statistically different from zero. Effect sizes are based on standardized latent variables. The figure shows the standardized mean differences and their 95% confidence intervals.

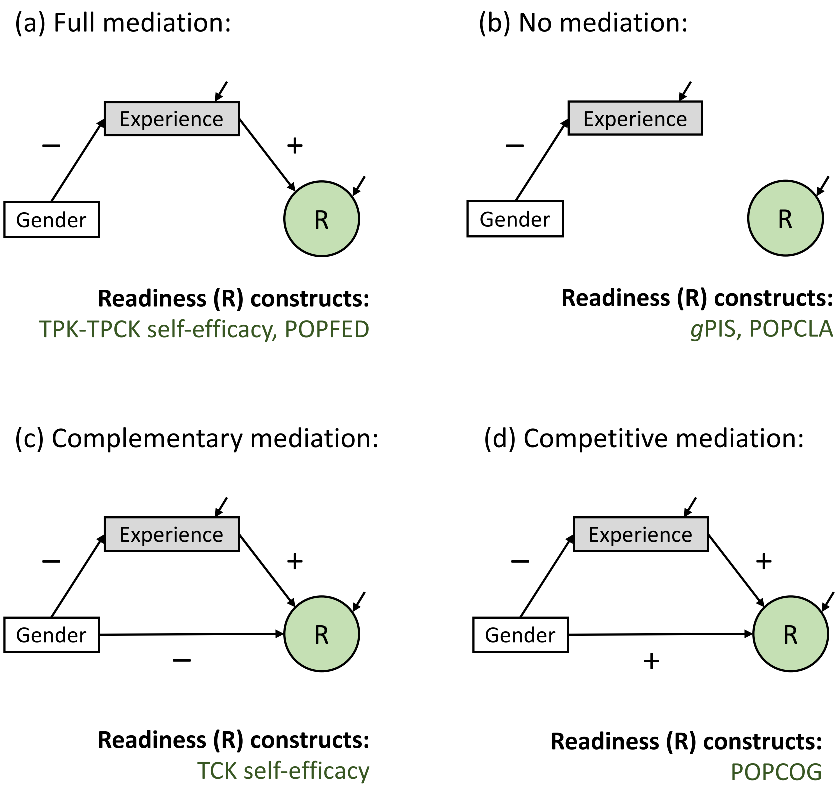

Fig. 4. Mediation Models Describing Gender Differences in Readiness via OTL Experience. *Note.* The positive and negative signs indicate the direction of the direct effects in the model. Readiness constructs are represented by the grey circles. *g*PIS = General factor representing perceived institutional support, POPFED = Perceived online teaching presence: Student feedback, POPCOG = Perceived online teaching presence: Cognitive activation, POPCLA = Perceived online teaching presence: Clarity of instruction, TCK = Technological content knowledge, TPK-TPCK = TPK and TPCK self-efficacy, TPK = Technological pedagogical knowledge, TPCK = Technological pedagogical content knowledge. The detailed measurement models of the readiness constructs (in green) are not shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

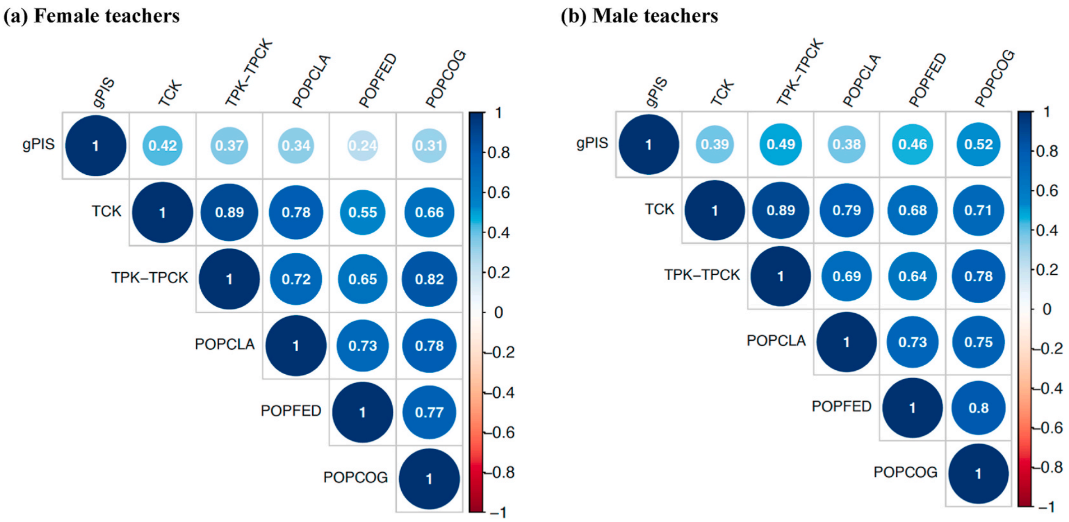

Fig. 5. Correlations among the Readiness Constructs across Gender. *Note.* Readiness constructs are represented by the respective latent variables in the strict invariance model (for model fit indices, see Table 3). gPIS = General factor representing perceived institutional support, TCK = TCK self-efficacy, TPK-TPCK = TPK and TPCK self-efficacy, TPK = Technological pedagogical knowledge, TPCK = Technological pedagogical content knowledge, POPFED = Perceived online teaching presence: Student feedback, POPCLA = Perceived online teaching presence: Clarity of instruction, POPCOG = Perceived online teaching presence: Cognitive activation. All correlations are significantly different from zero ($p < .01$).

6. Discussion

6.1. Gender differences in OTL readiness levels exist, are small, and vary across readiness constructs

Our study has shown that gender differences in teachers' OTL readiness exist, pointing to a digital gender divide in readiness constructs (Šabić et al., 2021). This finding indicates that the striving for equality in perceived readiness for OTL may require some tailored support, for instance, via professional development that addresses the digital gender divides (Bolliger & Halupa, 2022). Given that some readiness constructs are malleable (e.g., Koh et al., 2010; Rienties et al., 2013), closing these divides seems possible (Li, 2016).

Notably, gender differences occurred in TCK self-efficacy and cognitive activation practices. Together with Lauermann and König (2016), we argue that these differences have at least two interpretations: First, gender differences in the two readiness constructs could be due to gender differences in teachers' mastery experiences with OTL and perceived gender roles. Such experiences are key to developing positive self-beliefs about one's teaching capabilities (Morris et al., 2017). Huffman et al. (2013) showed that technological self-efficacy—a self-belief that relies on mastery experiences—is partly due to a person's understanding of gender roles, specifically masculinity. Second, teachers are exposed to subject cultures and socializations that can form teaching practices and beliefs through the lenses of gender roles. Implementing these teaching practices may differ across gender in the orientation toward mastery or performance. Despite these two interpretations, we argue that in-depth and longitudinal studies are needed to examine the causes, evolution, and development of gender differences in OTL readiness.

We also observed that gender effects varied in size and direction across readiness constructs—that is, not all readiness constructs exhibited these differences. This finding testifies to the construct specificity of digital gender divides (Gómez-Trigueros & Yáñez de Aldecoa, 2021). Similarly, in their secondary analysis of ICILS 2013, Scherer and Siddiq (2015) found that gender differences varied across teaching self-efficacy constructs. In our study, we found differences for TCK self-efficacy and cognitive activation, yet not for the other readiness constructs. This finding has several interpretations: (a) Gender differences in TCK self-efficacy were in the expected direction, with men showing higher self-efficacy than women (Gómez-Trigueros & Yáñez de Aldecoa, 2021). (b) In comparison to previously reported effect sizes, gender differences in TCK self-efficacy were small (see 2.2.1). This might be due to the heterogeneity of teachers in the sample who were teaching in different countries and cultures. However, this explanation needs to be substantiated with larger and representative teacher samples. (c) Concerning TPACK self-efficacy, no differences existed in the pedagogical dimensions, yet in the more content-related aspects of OTL. One may hypothesize that gender roles or stereotypes surface more likely in the subject-lean and content-related areas of teaching (Koh et al., 2010). However, we believe that this hypothesis requires further testing, especially because the extant literature indicated that gender differences can occur in the pedagogical areas as well (e.g., Ergen et al., 2019). (d) The opposite direction of gender effects for cognitive activation also requires further investigation, although prior research indicated that women implement more often interactive and activating teaching practices (Nikolopoulou & Kousloglou, 2022; Perera & John, 2020). (e) Finally, women and men reported similar support at their institutions. These similarities may be due to the provision of the same technological and pedagogical support to women and men and perceptions thereof. In contrast to self-beliefs and reported teaching practices, both of which rely on perceptions of one's capabilities and actions, perceived support relies on perceptions of *external* and contextual opportunities—thus, perceived support is part of a different belief system (Lawson et al., 2019). Overall, a digital gender divide in teachers' OTL readiness seems to exist, yet not for all readiness constructs.

6.2. Gender differences in OTL readiness levels can Be prone to measurement bias

Our study revealed that the measurement of OTL readiness was comparable across gender, yet not to the full extent. Given that some readiness indicators had different response probabilities after controlling for gender differences in the readiness constructs, differential item functioning existed. This finding has at least two implications: First, reported gender differences in OTL readiness without considering DIF may not be credible, and the resultant inferences drawn from them may not be valid (Hatlevik et al., 2017; Scherer & Siddiq, 2015). This is due to the fact that observed gender differences in readiness constructs do not only reflect gender differences in the "true" readiness scores but also differences in the response probabilities of the indicators (Millsap, 2011). To rule out the latter, controlling this measurement bias is essential for examining, reporting, and interpreting gender differences in OTL readiness and, ultimately, for crafting a validity argument behind digital gender divides (Büchi et al., 2015; Eagly & Revelle, 2022).

Second, the directions of DIF (i.e., in favor of women or men) are hardly predictable, unless evidence-based theories on the design elements of readiness indicators exist (Bundsgaard, 2019). In our study, three of four DIF items referred to student feedback and communication. It is likely that these are areas in which teaching practices differ in favor of women. At the same time, these practices were self-reported, so that actual differences in teaching practices may be camouflaged by differences in teachers' perceptions of what happens in classrooms (Wagner et al., 2016). We argue that the substantive causes of DIF in readiness indicators need to be further examined to build comprehensive theories that inform the design of readiness measures.

6.3. Gender differences in OTL readiness levels can Be partly explained by experience

As noted earlier, teachers' years of experience with OTL explained gender differences for most readiness constructs. One explanation of this finding may refer to the possible gender differences in the sources of self-efficacy, such as mastery experiences with OTL which could have been gained during teacher education or professional development (Klassen & Chiu, 2010).

In our study, different types of mediation models described the interplay between teachers' OTL experience and gender differences in OTL readiness. For the pedagogical dimensions of TPACK self-efficacy and feedback-oriented teaching practices, gender differences in these readiness constructs were initially insignificant beforehand. However, teachers' prior experience with OTL fully explained the gender differences in TPK-TPCK self-efficacy and POPFED (see Fig. 4). This finding suggests that OTL experience offers a possible mechanism and pathway through which gender differences can operate. To some extent, this finding is not surprising, because prior mastery experiences are sources of teachers' self-efficacy (Morris et al., 2017) and form the basis for high-quality teaching practices (Holzberger et al., 2013). However, we consider the full mediation result surprising, because it points to an experience rather than a readiness divide between the genders (Ilomäki, 2011; Teo et al., 2015). For TCK self-efficacy—the content-oriented dimension of TPACK self-efficacy—gender differences were not fully but partially explained by experience (about 17% of the total variation in readiness), and thus point to an experience *and* a readiness divide *complementing* each other. This observation is not unusual: van Dijk (2020) argued that digital gender divides do not exist in isolation but in conjunction with other divides. For cognitive activation practices, these two divides exist as well; yet, the direct and indirect effects cancelled each other out, to some extent (Henseler, 2021). In this case, OTL experience served as a *competitive* explanation for the readiness divide. Finally, for perceived institutional support and instructional clarity, no such mediation occurred, and only an experience divide existed. These findings show that the role OTL experience plays for the gender differences in readiness can vary across readiness constructs. Despite this variation, however, experience offers a possible mechanism and explanation for gender differences in OTL readiness. We therefore encourage researchers to consider reporting readiness divides in light of possible experience divides across gender. Moreover, professional development activities aimed at closing digital gender divides in OTL readiness could be tailored to teachers' OTL experience.

6.4. Gender differences can exist in the associations among OTL readiness constructs

Our study highlighted that gender differences do not only exist in the levels of teachers' OTL readiness but also in the associations among readiness constructs. More specifically, unequal factor correlations were sources of measurement non-invariance beyond the identified DIF items. This finding has several implications: First, gender differences can manifest in several types of parameters describing the readiness measurement models rather than only the construct means. The latter are typically reported in readiness research across gender (see Supplementary Material S1), and we encourage researchers in the field to extend their exploration of possible gender differences to other, construct-relevant sources. We also argue that understanding the possible causes and effects of gender differences in OTL readiness requires detailed information about where these differences lie, especially in order to rule out or control for the non-invariance of mere measurement properties (Millsap, 2011).

Second, differences in factor correlations indicate structural non-invariance and can compromise the comparisons of relations to other variables (Brown, 2015). For instance, if researchers observed gender differences in the relations between OTL readiness and student learning, these differences may be due to the structural non-invariance rather than to "true" differences. Hence, examining the invariance of the associations among readiness constructs is key to drawing valid inferences on possible gender differences in relations to other constructs (Hanham et al., 2021).

Third, differential construct associations suggest that the nomological nets—that is, networks describing the connections between latent and observed variables and between latent variables (Preckel & Brunner, 2017)—differ across gender. Such differences further suggest that the interplay between readiness constructs is gender-specific. Notably, the correlations between perceived institutional support and all other readiness constructs were weaker for women than for men. As noted earlier, teachers' perceptions of the institutional support they receive may be conceptually more distinct from the perceptions of teaching practices and competences—that is, perceptions of one's behavior and skills—for female teachers. These differences also testify to the existence of different readiness profiles across gender: high levels of PIS may not go together with high levels of other readiness dimensions for women but for men. Another interpretation refers to the sources of the perceptions of one's behavior and skills: Women's technology-related self-efficacy and teaching practices may rely less on the external support but on other factors, such as individual characteristics and mastery experiences (Scherer & Siddiq, 2015).

6.5. Limitations and future directions

The present study has several limitations: First, the insights gained from the three perspectives in our study were based on cross-sectional teacher data. While this does not represent a limitation per se, longitudinal data extensions could shed further light on the possible gender differences in the *development* of OTL readiness over time. Second, the present study was primarily aimed at illustrating possible gender differences in teacher readiness, the relations among its dimensions, and the relations among its indicators. While the respective findings identify which differences and similarities may exist, they do not explain the underlying mechanisms. For instance, we assumed that OTL experience mediated the gender differences. One could however also assume that gender may moderate the experience-readiness relation (Scherer et al., 2022). Causal study designs that include additional explanatory variables at different levels, such as gender roles, cultural orientation, indicators of country differences (e.g., gender equality indices), or detailed information about the online teaching practices in (digital) classrooms (e.g., Huffman et al., 2013; Scherer et al., 2021) could uncover possible causes and processes in future studies. Third, we relied on a common yet restrictive definition of teachers' gender as the identified sex. However, we believe that gender roles and identities could help understand the nature of the gender differences and similarities we have found in our study (Huffman et al., 2013).

7. Conclusion and implications

In the present study, we uncovered, quantified, and explained the gender differences in readiness for OTL in an international sample of higher-education teachers. Our findings have several implications for the field of OTL: First, gender differences in OTL exist but vary in both direction and size across readiness constructs. Hence, to uncover possible differences or similarities across gender, we argue that readiness measures should capture multiple constructs, such as self-efficacy, teaching practices, or perceived institutional support (see also Hung, 2016; Scherer & Siddiq, 2015). Second, gender differences occurred in TPACK self-efficacy and perceived online teaching presence. In our view, this finding implies that (a) women and men perceive their success in implementing teaching practices successfully and the respective teaching skills differently; (b) women and men may have different needs for professional development that is aimed at supporting their perceptions and beliefs; and (c) a digital gender divide exists for higher-education teachers in the context of OTL readiness. Third, we obtained evidence that gender differences in OTL readiness were at least partly due to gender differences in teachers' OTL experience. As a consequence, we argue that (a) gender differences may not be inherent per se but due to different mastery experiences with OTL; and (b) research on gender differences in OTL readiness should control for teachers' OTL experience. Fourth, gender differences occurred not only in readiness levels but also in the associations among readiness constructs. This implies that parts of the readiness nomological net differed between women and men and that the readiness constructs may thus relate differently to other constructs (see also Marsh et al., 2013). Overall, we argue that gender differences in OTL readiness are complex. However, accounting for measurement bias, including teachers' OTL experience as a possible mediator, and examining these differences in the readiness levels *and* construct associations can help uncover, quantify, and explain them.

Our findings have several implications for practice, in particular for designing and providing professional development. In the short term, there is a need for providing educators both technical *and* pedagogical support as emphasized by other recent studies (e.g., Paliwal & Singh, 2021; Scherer et al., 2023), assuring that both female and male educators are given the opportunity to develop technical skills and pedagogical practices to support student-active learning. Our results on the close relation between experience and gender differences in readiness constructs point to the need for comprehensive and professional development programs. Seemingly, if men volunteer more often for or are selected for leading online teaching classes compared to women, this might have consequences in the long term—for instance, increasing the gender divide in favor of male teachers (Fütterer et al., 2023). Hence, another implication might be that institutional leadership needs to be aware of such issues and assure that all educators are provided equal opportunities and professional development programs for OTL (Raman & Thannimalai, 2019).

Ultimately, our findings contribute to extending the theoretical and empirical perspectives on gender differences in OTL readiness and could inform the development of support and professional development programs that strive for closing digital gender divides.

Credit author statement

Ronny Scherer: Conceptualization, methodology, software, formal analysis, investigation, data curation, writing-original draft, writing-review & editing, visualization; **Fazilat Siddiq:** Conceptualization, methodology, investigation, resources, writing-review & editing; **Sarah K. Howard:** Conceptualization, methodology, software, investigation, resources, data curation, writing-review & editing, project administration; **Jo Tondeur:** Conceptualization, methodology, investigation, resources, data curation, writing-review & editing, project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compedu.2023.104774.

References

Adnan, M. (2017). Professional development in the transition to online teaching: The voice of entrant online instructors. *ReCALL, 30*(1), 88–111. https://doi.org/10.1017/S0958344017000106

AERA, APA, & NCME. (2014). *Standards for educational and psychological testing: National council on measurement in education*. American Educational Research Association.

Alamri, H. A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environments in higher education. *TechTrends, 65*(1), 62–78. https://doi.org/10.1007/s11528-020-00530-3

Archambault, L., & Crippen, K. (2009). Examining TPACK among K-12 online distance educators in the United States. *Contemporary Issues in Technology and Teacher Education, 9*(1), 71–88.

Backfisch, I., Lachner, A., Hische, C., Loose, F., & Scheiter, K. (2020). Professional knowledge or motivation? Investigating the role of teachers' expertise on the quality of technology-enhanced lesson plans. *Learning and Instruction, 66*, Article 101300. https://doi.org/10.1016/j.learninstruc.2019.101300

Barton, E. A., & Dexter, S. (2020). Sources of teachers' self-efficacy for technology integration from formal, informal, and independent professional learning. *Educational Technology Research & Development, 68*(1), 89–108. https://doi.org/10.1007/s11423-019-09671-6

Bauer, D. J. (2017). A more general model for testing measurement invariance and differential item functioning. *Psychological Methods, 22*(3), 507–526. https://doi.org/10.1037/met0000077

Blömeke, S., Nilsen, T., & Scherer, R. (2021). School innovativeness is associated with enhanced teacher collaboration, innovative classroom practices, and job satisfaction. *Journal of Educational Psychology*. https://doi.org/10.1037/edu0000668

Bolliger, D. U., & Halupa, C. (2022). An investigation of instructors' online teaching readiness. *TechTrends, 66*(2), 185–195. https://doi.org/10.1007/s11528-021-00654-0

Borokhovski, E., Pickup, D. I., El Saadi, L., Rabah, J., & Tamim, R. M. (2018). *Gender and ICT: Meta-analysis and systematic review*. Commonwealth of Learning. http://hdl.handle.net/11599/3089.

Brinkley-Etzkorn, K. E. (2018). Learning to teach online: Measuring the influence of faculty development training on teaching effectiveness through a TPACK lens. *The Internet and Higher Education, 38*, 28–35. https://doi.org/10.1016/j.iheduc.2018.04.004

Brooks, D. C., & Grajek, S. (2020). Faculty readiness to begin fully remote teaching. *Educause Review*. https://er.educause.edu/blogs/2020/3/faculty-readiness-to-begin-fully-remote-teaching.

Brown, T. A. (2015). *Confirmatory factor analysis for applied research* (2nd ed.). The Guilford Press.

Büchi, M., Just, N., & Latzer, M. (2015). Modeling the second-level digital divide: A five-country study of social differences in internet use. *New Media & Society, 18*(11), 2703–2722. https://doi.org/10.1177/1461444815604154

Bundsgaard, J. (2019). DIF as a pedagogical tool: Analysis of item characteristics in ICILS to understand what students are struggling with. *Large-scale Assessments in Education, 7*.

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computers & Education, 105*, 1–13. https://doi.org/10.1016/j.compedu.2016.11.003

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Chou, H.-L., & Chou, C. (2021). A multigroup analysis of factors underlying teachers' technostress and their continuance intention toward online teaching. *Computers & Education, 175*, Article 104335. https://doi.org/10.1016/j.compedu.2021.104335

Chou, C.-L., Hung, M.-L., Tsai, C.-W., & Chang, Y.-C. (2020). Developing and validating a scale for measuring teachers' readiness for flipped classrooms in junior high schools. *British Journal of Educational Technology, 51*(4), 1420–1435. https://doi.org/10.1111/bjet.12895

Chua, Y. P., & Chua, Y. P. (2017). How are e-leadership practices in implementing a school virtual learning environment enhanced? A grounded model study. *Computers & Education, 109*, 109–121. https://doi.org/10.1016/j.compedu.2017.02.012

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin, 52*(4), 281–302. https://doi.org/10.1037/h0040957

Cutri, R. M., & Mena, J. (2020). A critical reconceptualization of faculty readiness for online teaching. *Distance Education, 41*(3), 361–380. https://doi.org/10.1080/01587919.2020.1763167

Cutri, R. M., Mena, J., & Whiting, E. F. (2020). Faculty readiness for online crisis teaching: Transitioning to online teaching during the COVID-19 pandemic. *European Journal of Teacher Education, 43*(4), 523–541. https://doi.org/10.1080/02619768.2020.1815702

Damşa, C., Langford, M., Uehara, D., & Scherer, R. (2021). Teachers' agency and online education in times of crisis. *Computers in Human Behavior, 121*, Article 106793. https://doi.org/10.1016/j.chb.2021.106793

van Dijk, J. A. G. M. (2020). *The digital divide*. Wiley.

Eagly, A. H., & Revelle, W. (2022). Understanding the magnitude of psychological differences between women and men requires seeing the forest and the trees. *Perspectives on Psychological Science*. https://doi.org/10.1177/17456916211046006, 17456916211046006.

Enders, C. K. (2010). *Applied missing data analysis*. Guilford Press.

Ergen, B., Yanpar Yelken, T., & Kanadli, S. (2019). A meta-analysis of research on technological pedagogical content knowledge by gender. *Contemporary Educational Technology, 10*(4), 358–380. https://doi.org/10.30935/cet.634182

Eslaminejad, T., Masood, M., & Ngah, N. A. (2010). Assessment of instructors' readiness for implementing e-learning in continuing medical education in Iran. *Medical Teacher, 32*(10), e407–e412. https://doi.org/10.3109/0142159X.2010.496006

Flora, D. B. (2020). Your coefficient alpha is probably wrong, but which coefficient omega is right? A tutorial on using R to obtain better reliability estimates. *Advances in Methods and Practices in Psychological Science, 3*(4), 484–501. https://doi.org/10.1177/2515245920951747

Fütterer, T., Scherer, R., Scheiter, K., Stürmer, K., & Lachner, A. (2023). Will, skills, or conscientiousness: What predicts teachers' intentions to participate in technology-related professional development? *Computers & Education, 198*, Article 104756. https://doi.org/10.1016/j.compedu.2023.104756

Gebhardt, E., Thomson, S., Ainley, J., & Hillman, K. (2019). In *Gender differences in computer and information literacy: An in-depth analysis of data from ICILS. IEA research for education*. International Association for the Evaluation of Educational Achievement. Vol. 8.

Gómez-Trigueros, I. M., & Yáñez de Aldecoa, C. (2021). The digital gender gap in teacher education: The TPACK framework for the 21st century. *European Journal of Investigation in Health, Psychology and Education, 11*(4). https://doi.org/10.3390/ejihpe11040097

Graham, C. R., Woodfield, W., & Harrison, J. B. (2013). A framework for institutional adoption and implementation of blended learning in higher education. *The Internet and Higher Education, 18*, 4–14. https://doi.org/10.1016/j.iheduc.2012.09.003

Gurley, L. E. (2018). Educators' preparation to teach, perceived teaching presence, and perceived teaching presence behaviors in blended and online learning environments. *Online Learning Journal, 22*(2), 197–220. https://doi.org/10.24059/olj.v22i2.1255

Hahn, S., Pfeifer, A., & Kunina-Habenicht, O. (2022). Multiple facets of self-rated digital competencies of pre-service teachers: A pilot study on the nomological network, empirical structure, and gender differences [original research]. *Frontiers in Education, 7*. https://doi.org/10.3389/feduc.2022.999679

Hanham, J., Lee, C. B., & Teo, T. (2021). The influence of technology acceptance, academic self-efficacy, and gender on academic achievement through online tutoring. *Computers & Education, 172*, Article 104252. https://doi.org/10.1016/j.compedu.2021.104252

Hatlevik, O. E., Scherer, R., & Christophersen, K.-A. (2017). Moving beyond the study of gender differences: An analysis of measurement invariance and differential item functioning of an ICT literacy scale. *Computers & Education, 113*, 280–293. https://doi.org/10.1016/j.compedu.2017.06.003

Henseler, J. (2021). *Composite-based structural equation modeling: Analyzing latent and emergent variables*. Guilford Press.

Holzberger, D., Philipp, A., & Kunter, M. (2013). How teachers' self-efficacy is related to instructional quality: A longitudinal analysis. *Journal of Educational Psychology, 105*(3), 774–786. https://doi.org/10.1037/a0032198

Howard, S. K., Tondeur, J., Hutchinson, N., Scherer, R., & Siddiq, F. (2022). *A t(r)opical journey: Using text mining to explore teachers' experiences in the great online transition society for information technology & teacher education (SITE) international conference* (San Diego, USA).

Howard, S. K., Tondeur, J., Siddiq, F., & Scherer, R. (2020). Ready, set, go! Profiling teachers' readiness for online teaching in secondary education. *Technology, Pedagogy and Education*, 1–18. https://doi.org/10.1080/1475939X.2020.1839543

Hu, L.t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. *Computers in Human Behavior, 29*(4), 1779–1786. https://doi.org/10.1016/j.chb.2013.02.012

Hung, M.-L. (2016). Teacher readiness for online learning: Scale development and teacher perceptions. *Computers & Education, 94*, 120–133. https://doi.org/10.1016/j.compedu.2015.11.012

Ilomäki, L. (2011). Does gender have a role in ICT among Finnish teachers and students? *Scandinavian Journal of Educational Research, 55*(3), 325–340. https://doi.org/10.1080/00313831.2011.576910

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., & Rosseel, Y. (2021). semTools: Useful tools for structural equation modeling. *R package version 0.5-5*. https://CRAN.R-project.org/package=semTools.

Klassen, R. M., & Chiu, M. M. (2010). Effects on teachers' self-efficacy and job satisfaction: Teacher gender, years of experience, and job stress. *Journal of Educational Psychology, 102*(3), 741–756. https://doi.org/10.1037/a0019237

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Koehler, M. J., Mishra, P., Kereluik, K., Shin, T. S., & Graham, C. R. (2014). The technological pedagogical content knowledge framework. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 101–111). Springer. https://doi.org/10.1007/978-1-4614-3185-5_9.

Koh, J. H. L., Chai, C. S., & Tsai, C. C. (2010). Examining the technological pedagogical content knowledge of Singapore pre-service teachers with a large-scale survey. *Journal of Computer Assisted Learning, 26*(6), 563–573. https://doi.org/10.1111/j.1365-2729.2010.00372.x

Korlat, S., Kollmayer, M., Holzer, J., Lüftenegger, M., Pelikan, E. R., Schober, B., & Spiel, C. (2021). Gender differences in digital learning during COVID-19: Competence beliefs, intrinsic value, learning engagement, and perceived teacher support. *Frontiers in Psychology, 12*(849). https://doi.org/10.3389/fpsyg.2021.637776

Kreijns, K., Xu, K., & Weidlich, J. (2022). Social presence: Conceptualization and measurement. *Educational Psychology Review, 34*(1), 139–170. https://doi.org/10.1007/s10648-021-09623-8

Lachner, A., Backfisch, I., & Stürmer, K. (2019). A test-based approach of modeling and measuring technological pedagogical knowledge. *Computers & Education, 142*, Article 103645. https://doi.org/10.1016/j.compedu.2019.103645

Landino, R. A., & Owen, S. V. (1988). Self-efficacy in university faculty. *Journal of Vocational Behavior, 33*(1), 1–14. https://doi.org/10.1016/0001-8791(88)90030-9

Lauermann, F., & König, J. (2016). Teachers' professional competence and wellbeing: Understanding the links between general pedagogical knowledge, self-efficacy and burnout. *Learning and Instruction, 45*, 9–19. https://doi.org/10.1016/j.learninstruc.2016.06.006

Law, K. M. Y., Geng, S., & Li, T. (2019). Student enrollment, motivation and learning performance in a blended learning environment: The mediating effects of social, teaching, and cognitive presence. *Computers & Education, 136*, 1–12. https://doi.org/10.1016/j.compedu.2019.02.021

Lawson, M. J., Vosniadou, S., Van Deur, P., Wyra, M., & Jeffries, D. (2019). Teachers' and students' belief systems about the self-regulation of learning. *Educational Psychology Review, 31*(1), 223–251. https://doi.org/10.1007/s10648-018-9453-7

Li, Y. (2016). Is teacher professional development an effective way to mitigate teachers' gender differences in technology? Result from a statewide teacher professional development program. *Journal of Education and Training Studies, 4*(2), 21–26. https://doi.org/10.11114/jets.v4i2.1124

Marsh, H. W., Hau, K.-T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing hu and bentler's (1999) findings. *Structural Equation Modeling, 11*(3), 320–341. https://doi.org/10.1207/s15328007sem1103_2

Marsh, H. W., Muthén, B., Asparouhov, T., Lüdtke, O., Robitzsch, A., Morin, A. J. S., & Trautwein, U. (2009). Exploratory structural equation modeling, integrating CFA and EFA: Application to students' evaluations of university teaching. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(3), 439–476. https://doi.org/10.1080/10705510903008220

Marsh, H. W., Nagengast, B., & Morin, A. J. S. (2013). Measurement invariance of big-five factors over the life span: ESEM tests of gender, age, plasticity, maturity, and la dolce vita effects. *Developmental Psychology, 49*(6), 1194–1218. https://doi.org/10.1037/a0026913

Martin, F., Budhrani, K., & Wang, C. (2019). Examining faculty perception of their readiness to teach online. *Online Learning Journal, 23*(3), 97–119. https://doi.org/10.24059/olj.v23i3.1555

McNeish, D., & Wolf, M. G. (2021). Dynamic fit index cutoffs for confirmatory factor analysis models. *Psychological Methods*. https://doi.org/10.1037/met0000425

Millsap, R. E. (2011). *Statistical approaches to measurement invariance*. Routledge/Taylor & Francis Group.

Mittal, A., Mantri, A., Tandon, U., & Dwivedi, Y. K. (2021). A unified perspective on the adoption of online teaching in higher education during the COVID-19 pandemic. *Information Discovery and Delivery, 50*(2), 117–132. https://doi.org/10.1108/IDD-09-2020-0114

Morris, D. B., Usher, E. L., & Chen, J. A. (2017). Reconceptualizing the sources of teaching self-efficacy: A critical review of emerging literature. *Educational Psychology Review, 29*(4), 795–833. https://doi.org/10.1007/s10648-016-9378-y

Nikolopoulou, K., & Kousloglou, M. (2022). Online teaching in COVID-19 pandemic: Secondary school teachers' beliefs on teaching presence and school support. *Education Sciences, 12*(3), 216. https://doi.org/10.3390/educsci12030216

Núñez-Canal, M., de Obesso, M.d. l. M., & Pérez-Rivero, C. A. (2022). New challenges in higher education: A study of the digital competence of educators in covid times. *Technological Forecasting and Social Change, 174*, Article 121270. https://doi.org/10.1016/j.techfore.2021.121270

Özgür, H. (2020). Relationships between teachers' technostress, technological pedagogical content knowledge (TPACK), school support and demographic variables: A structural equation modeling. *Computers in Human Behavior, 112*, Article 106468. https://doi.org/10.1016/j.chb.2020.106468

Paliwal, M., & Singh, A. (2021). Teacher readiness for online teaching-learning during COVID −19 outbreak: A study of Indian institutions of higher education. *Interactive Technology and Smart Education*. https://doi.org/10.1108/ITSE-07-2020-0118

Perera, H. N., & John, J. E. (2020). Teachers' self-efficacy beliefs for teaching math: Relations with teacher and student outcomes. *Contemporary Educational Psychology, 61*, Article 101842. https://doi.org/10.1016/j.cedpsych.2020.101842

Philipsen, B. (2018). *Teacher professional development for online and blended learning in adult education and training [Doctoral Dissertation*. Brussels, Belgium: Vrije Universiteit Brussel.

Philipsen, B., Tondeur, J., Scherer, R., Pynoo, B., & Zhu, C. (2022). Measuring institutional support for online and blended learning professional development: Validating an instrument that examines teachers' perceptions. *International Journal of Research and Method in Education, 45*(2), 164–179. https://doi.org/10.1080/1743727X.2021.1926973

Preckel, F., & Brunner, M. (2017). Nomological nets. In V. Zeigler-Hill, & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences* (pp. 1–4). Springer International Publishing. https://doi.org/10.1007/978-3-319-28099-8_1334-1.

Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review, 41*, 71–90. https://doi.org/10.1016/j.dr.2016.06.004

Qazi, A., Hasan, N., Abayomi-Alli, O., Hardaker, G., Scherer, R., Sarker, Y., Kumar Paul, S., & Maitama, J. Z. (2022). Gender differences in information and communication technology use & skills: A systematic review and meta-analysis. *Education and Information Technologies, 27*(3), 4225–4258. https://doi.org/10.1007/s10639-021-10775-x

Raman, A., & Thannimalai, R. (2019). Importance of technology leadership for technology integration: Gender and professional development perspective. *Sage Open, 9*(4), Article 2158244019893707. https://doi.org/10.1177/2158244019893707

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L., & Koole, M. (2020). Online university teaching during and after the covid-19 crisis: Refocusing teacher presence and learning activity. *Postdigital Science and Education*. https://doi.org/10.1007/s42438-020-00155-y

Rhemtulla, M., Brosseau-Liard, P.É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods, 17*(3), 354–373. https://doi.org/10.1037/a0029315

Rienties, B., Brouwer, N., Bohle Carbonell, K., Townsend, D., Rozendal, A.-P., van der Loo, J., Dekker, P., & Lygo-Baker, S. (2013). Online training of TPACK skills of higher education scholars: A cross-institutional impact study. *European Journal of Teacher Education, 36*(4), 480–495. https://doi.org/10.1080/02619768.2013.801073

Robitzsch, A. (2020). Why ordinal variables can (almost) always Be treated as continuous variables: Clarifying assumptions of robust continuous and ordinal factor analysis estimation methods. *Frontiers in Education, 5*. https://doi.org/10.3389/feduc.2020.589965

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 1*(2). https://doi.org/10.18637/jss.v048.i02

Šabić, J., Baranović, B., & Rogošić, S. (2021). Teachers' self-efficacy for using information and communication technology: The interaction effect of gender and age. *Informatics in Education*. https://doi.org/10.15388/infedu.2022.11

Saikkonen, L., & Kaarakainen, M.-T. (2021). Multivariate analysis of teachers' digital information skills - the importance of available resources. *Computers & Education, 168*, Article 104206. https://doi.org/10.1016/j.compedu.2021.104206

Savalei, V. (2018). On the computation of the RMSEA and CFI from the mean-and-variance corrected test statistic with nonnormal data in SEM. *Multivariate Behavioral Research, 53*(3), 419–429. https://doi.org/10.1080/00273171.2018.1455142

Savalei, V., & Rosseel, Y. (2022). Computational options for standard errors and test statistics with incomplete normal and nonnormal data in SEM. *Structural Equation Modeling: A Multidisciplinary Journal, 29*(2), 163–181. https://doi.org/10.1080/10705511.2021.1877548

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F. (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? *Computers in Human Behavior, 118*, Article 106675. https://doi.org/10.1016/j.chb.2020.106675

Scherer, R., & Siddiq, F. (2015). Revisiting teachers' computer self-efficacy: A differentiated view on gender differences. *Computers in Human Behavior, 53*, 48–57. https://doi.org/10.1016/j.chb.2015.06.038

Scherer, R., Siddiq, F., Howard, S. K., & Tondeur, J. (2022). *The More Experienced, the Better Prepared? New Evidence on the Relation between Teachers' Experience and their Readiness for Online Teaching and Learning*. https://doi.org/10.31234/osf.io/zm9eh. *PsyArXiV Preprints*.

Scherer, R., Siddiq, F., Howard, S. K., & Tondeur, J. (2023). The more experienced, the better prepared? New evidence on the relation between teachers' experience and their readiness for online teaching and learning. *Computers in Human Behavior, 139*, Article 107530. https://doi.org/10.1016/j.chb.2022.107530

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (tam): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Scherer, R., & Teo, T. (2019). Unpacking teachers' intentions to integrate technology: A meta-analysis. *Educational Research Review, 27*, 90–109. https://doi.org/10.1016/j.edurev.2019.03.001

Scherer, R., Tondeur, J., & Siddiq, F. (2017). On the quest for validity: Testing the factor structure and measurement invariance of the technology-dimensions in the Technological, Pedagogical, and Content Knowledge (TPACK) model. *Computers & Education, 112*, 1–17. https://doi.org/10.1016/j.compedu.2017.04.012

Schmid, M., Brianza, E., & Petko, D. (2020). Developing a short assessment instrument for Technological Pedagogical Content Knowledge (TPACK.xs) and comparing the factor structure of an integrative and a transformative model. *Computers & Education, 157*, Article 103967. https://doi.org/10.1016/j.compedu.2020.103967

Shea, P., Sau Li, C., & Pickett, A. (2006). A study of teaching presence and student sense of learning community in fully online and web-enhanced college courses. *The Internet and Higher Education, 9*(3), 175–190. https://doi.org/10.1016/j.iheduc.2006.06.005

Shi, D., Lee, T., & Maydeu-Olivares, A. (2018). Understanding the model size effect on SEM fit indices. *Educational and Psychological Measurement, 79*(2), 310–334. https://doi.org/10.1177/0013164418783530

Siddiq, F., & Scherer, R. (2016). The relation between teachers' emphasis on the development of students' digital information and communication skills and computer self-efficacy: The moderating roles of age and gender. *Large-scale Assessments in Education, 4*(1), 17. https://doi.org/10.1186/s40536-016-0032-4

Teo, T. (2014). Unpacking teachers' acceptance of technology: Tests of measurement invariance and latent mean differences. *Computers & Education, 75*, 127–135. https://doi.org/10.1016/j.compedu.2014.01.014

Teo, T., Fan, X., & Du, J. (2015). Technology acceptance among pre-service teachers: Does gender matter? *Australasian Journal of Educational Technology, 31*(3), 235–251. https://doi.org/10.14742/ajet.1672

The World Bank. (2020). *Countries and economies*. The World Bank Group. Retrieved 01 September 2020 from https://data.worldbank.org/country.

Tondeur, J., Scherer, R., Baran, E., Siddiq, F., Valtonen, T., & Sointu, E. (2019). Teacher educators as gatekeepers: Preparing the next generation of teachers for technology integration in education. *British Journal of Educational Technology, 50*(3), 1189–1209. https://doi.org/10.1111/bjet.12748

Voogt, J., Fisser, P., Pareja Roblin, N., Tondeur, J., & van Braak, J. (2013). Technological pedagogical content knowledge – a review of the literature. *Journal of Computer Assisted Learning, 29*(2), 109–121. https://doi.org/10.1111/j.1365-2729.2012.00487.x

Wagner, W., Göllner, R., Werth, S., Voss, T., Schmitz, B., & Trautwein, U. (2016). Student and teacher ratings of instructional quality: Consistency of ratings over time, agreement, and predictive power. *Journal of Educational Psychology, 108*(5), 705–721. https://doi.org/10.1037/edu0000075

Wolf, M. G., & McNeish, D. (2020). Dynamic model fit. In *R shiny application (version 1.1.0)*. https://dynamicfit.app/cfa.

Woods, C. M. (2009). Evaluation of MIMIC-model methods for DIF testing with comparison to two-group analysis. *Multivariate Behavioral Research, 44*(1), 1–27. https://doi.org/10.1080/00273170802620121

Yuan, K.-H., & Bentler, P. M. (2000). Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology, 30*(1), 165–200. https://doi.org/10.1111/0081-1750.00078

Yu, H., Zhang, J., & Zou, R. (2021). A motivational mechanism framework for teachers' online informal learning and innovation during the COVID-19 pandemic. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.601200

Zeng, Y., Wang, Y., & Li, S. (2022). The relationship between teachers' information technology integration self-efficacy and TPACK: A meta-analysis [systematic review]. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.1091017